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Battery First: AI Control for Priority-Based Off-Grid Energy Management

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Abstract *– Off-grid solar systems encounter difficulties during low solar irradiance periods, particularly at night when photovoltaic generation stops. This study evaluates and compares the performance of five machine learning models Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine (RBF), and Decision Tree for prioritizing load cut-offs in AI to maintain critical loads during energy shortages. Data averaged hourly from an off-grid solar setup in Chiang Mai, Thailand, for 2024, included photovoltaic output, battery metrics, and categorized load usage during rainy, winter, and summer seasons. Models were trained on rainy season data and tested on winter, summer, and October datasets. We evaluated performance through MAE, RMSE, R^2, classification reports, F1-scores, and k-fold cross-validation to ensure stability. Results indicate that Random Forest and Gradient Boosting consistently reached the highest accuracy ($R^2 > 0.95$ in most seasons) with low MAE and RMSE, whereas Decision Tree and Logistic Regression showed more variability. AI-driven scenarios greatly improved nighttime battery performance over non-AI approaches, especially during the rainy season. This method enhances energy reliability and battery longevity in off-grid settings, but outcomes vary by location. Future research should explore a wider range of climates and load profiles.*

Keywords – AI-based load management, battery discharge prediction, energy prioritization, load prioritization, off-grid solar systems.

1. INTRODUCTION

Off-grid solar energy systems struggle to provide consistent power, especially at night when solar generation stops. During prolonged low solar irradiance, like the rainy season, battery reserves may fall short of supporting all connected loads. Without proper management, these issues can cause early battery to drain or total system failure, interrupting vital services and diminishing system reliability.

Recently, smart energy management methods have developed to tackle these issues, integrating real-time monitoring, predictive analytics, and adaptive control. Machine learning methods have proven effective in predicting energy availability and optimizing load prioritization according to battery status and consumption needs. Earlier research in microgrid and off-grid settings has shown that AI-driven control can minimize energy waste, increase operational hours, and improve resilience in changing weather conditions.

This research aims to create and assess an AI-based framework for prioritizing load cut-offs in off-grid solar systems, ensuring that essential loads stay operational at night by dynamically restricting non-essential usage.

The approach included gathering detailed hourly operational data from an off-grid solar setup in Chiang Mai, Thailand, covering photovoltaic output, battery condition, and categorized energy use. Various machine learning models were developed to forecast battery discharge time, and simulations were performed to evaluate system performance with AI-managed versus non-AI-managed load control strategies. Model accuracy was evaluated using MAE, RMSE, and R^2.

The findings show that the AI approach enhances system stability, increases nighttime energy availability, and lessens battery stress. This framework provides a scalable, affordable solution for energy-limited off-grid applications, showing great promise for use in rural and remote areas where reliability is essential for economic and social sustainability.

2. LITERATURE REVIEW

An extensive review of peer-reviewed literature was conducted to explore methods for enhancing energy reliability in off-grid systems, especially during nighttime when solar input is low or absent. Recent studies concentrated on AI-assisted energy forecasting, smart microgrid optimization, and energy prioritization strategies in low-resource settings. Sources included IEEE, Elsevier, and other indexed publications, concentrating on real-time energy management in off-grid or remote environments.

Only sources providing experimental validation or simulation-based analysis of AI techniques in power control were included. Literature showcasing machine learning (ML) models, energy management controllers,

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and predictive battery usage was prioritized. Selected contributions from Mohamed *et al.* [7], Sankarananth *et al.* [16], and Lissa *et al.* [17] were noted for their technical rigor and relevance in AI deployment within embedded or edge systems for intelligent load control.

The focus in the literature is using AI for load forecasting, classification, and managing energy storage to facilitate dynamic power allocation in limited off-grid systems. There is agreement on the effectiveness of ML models such as ANN, LSTM, and hybrid CNN-LSTM [7], [8], but discussions continue regarding the trade-off between model complexity and deploy ability in low-compute settings [20], [21]. A significant gap is the incorporation of AI-driven load shedding in systems facing limited connectivity and real-time processing limitations. Additionally, cybersecurity issues and model transparency (XAI) are still not thoroughly examined in off-grid environments. This method ensures system stability and prevents blackouts, keeping essential services running [1].

This review focuses on five key themes: (1) AI in load forecasting, (2) load classification and prioritization, (3) optimization of demand response, (4) management of energy storage and discharge, and (5) detection of anomalies in energy usage. Each area is examined via essential methodologies, practical uses, and the challenges faced. Limited Renewable Generation Solar PV systems, a common component of off-grid setups, do not generate electricity at night, reducing the available energy supply [2]. The review wraps up by synthesizing emerging trends and future research directions essential for advancing intelligent off-grid energy systems.

1. AI for Load Forecasting in Off-Grid Systems

Accurate load forecasting is essential for ensuring energy reliability at night. AI algorithms can predict energy demand by analysing historical consumption, weather conditions, and occupancy patterns [4]. Artificial Neural Networks (ANNs) [7] are commonly used for their capacity to learn complex nonlinear relationships. LSTM networks excel at capturing time-dependent usage trends [7], and hybrid models like CNN-LSTM enhance accuracy by integrating spatial and temporal feature learning [8].

2. Models for Load Classification and Prioritization

In constrained environments, energy efficiency relies on smart identification of load priorities. Rule-based systems provide clear-cut classification, yet machine learning techniques like decision trees and support vector machines are gaining traction for their ability to adapt to consumption patterns [6]. These models categorize and prioritize loads, allowing for immediate decisions to maintain power for critical services such as communication or medical devices in battery-constrained situations [4].

3. AI-Driven Demand Response Optimization

AI improves demand response (DR) strategies by analysing consumer profiles and adjusting or reducing demand accordingly. Methods like real-time dynamic pricing [9], [15], incentive-based programs [5], and direct load control [10] enable smart interaction with users or devices to reduce peak demand. These methods are especially important in off-grid microgrids, where sudden load spikes can quickly drain storage systems.

4. Control of Battery Energy Storage Systems (BESS)

Optimizing battery use is essential for nighttime load support. Predictive AI models anticipate energy generation and demand, allowing for proactive charging during daylight and strategic discharging at night [3]. SoC optimization models, using historical data, ensure battery operation stays within safe limits, preventing overcharge and deep discharge that can harm battery life [11]. AI manages the interplay between batteries and supercapacitors in hybrid storage systems to enhance energy delivery efficiency [12].

5. Anomaly Detection and Reducing Energy Waste

Energy use anomalies, often stemming from faulty devices or changes in behaviour, threaten energy reliability. Clustering algorithms like k-means identify outliers in load patterns [14], whereas autoencoder neural networks highlight deviations by reconstructing anticipated data from learned baselines [7]. ARIMA models for time-series forecasting help identify unexpected behaviour [8], which supports preventive maintenance and minimizes waste in energy-constrained systems [13].

6. AI-Driven Implementation Framework

Implementing AI-based cutoff load strategies successfully requires several stages: data collection [8], load classification [6], model training [7], system integration [6], and field validation [12]. Ongoing monitoring allows the model to adjust to changing patterns, and retraining with new datasets enhances performance progressively. Testing through simulation, along with staged deployment, ensures validation of robustness across different load conditions.

7. Evidence from Case Studies and Impact on Systems

Mohamed *et al.* [7] showcased a practical use of AI in forecasting and optimizing a hydrogen-powered microgrid, resulting in enhanced load matching and system reliability. Sankaranath *et al.* [16] utilized metaheuristic-AI models in smart grids for efficient power scheduling at reduced costs. Lissa *et al.* [17] demonstrated that deep reinforcement learning can enhance home energy systems by synchronizing PV output with indoor environmental control. These cases demonstrate AI's significant impact on energy distribution logic and priority management.

8. Measurable Advantages of AI Integration

Numerous studies indicate substantial improvements in system performance through AI-driven cutoff strategies. Improvements in efficiency arise from enhanced load-supply matching [18], and battery lifespan is prolonged via smart charging and discharging cycles [11]. AI improves occupant comfort by maintaining essential services during power limitations [17] and facilitates better integration of renewable energy sources [12]. AI can prevent blackouts and ensure a reliable power supply [19].

9. Challenges of Implementation in Off-Grid Settings

AI has great potential for off-grid energy management, but challenges remain. In numerous off-grid areas, data collection systems are lacking, and hardware limitations restrict the use of advanced AI models. A lack of local expertise in AI system development and maintenance creates additional challenges. Security is a major concern, as shown in [22], where risks like data tampering or unauthorized load manipulation in control systems require secure architectures and defence strategies to protect AI-enabled IoT deployments.

10. Directions for Future Research and Technology

New studies aim to enhance the accessibility and practicality of AI for remote applications. Edge computing allows models to operate locally, reducing reliance on cloud infrastructure [23]. Federated learning enables training without the need to transfer sensitive data [20], and explainable AI enhances trust and transparency in automated decision-making [21]. Reinforcement learning is increasingly recognized for its ability to adapt to real-time conditions and optimize continuously [16].

AI-driven load prioritization represents a significant improvement for off-grid energy systems, especially in boosting nighttime reliability when storage is limited. Literature indicates that improvements in forecasting, load classification, demand response, and storage optimization greatly enhance system resilience. Despite ongoing implementation challenges, particularly in resource-limited regions, research indicates a clear trend towards wider adoption of intelligent energy management solutions. Advancements in lightweight, explainable, and secure AI models will enhance sustainable energy autonomy for underserved communities.

3. METHODOLOGY

This research adopts a data-driven approach to optimize nighttime energy management in off-grid solar systems using AI-based load prioritization. The methodology integrates real-world energy data with predictive modeling to simulate battery performance under different load control strategies.

3.1 Research Design

The study employs a comparative experimental design that simulates two operational scenarios: one with traditional fixed load control, and the other using AI-driven dynamic prioritization. Load categories are segmented into three tiers based on criticality Internet and networking (1st), lighting (2nd), and USB/CCTV devices (3rd) to support intelligent shedding during low power availability.

The system architecture developed for this study is illustrated in Figure 1. The setup consists of an off-grid photovoltaic energy system equipped with a solar cell array connected to a charger controller. Energy harvested during the day is regulated by the controller and stored in a 13.2V $LiFePO_4$ battery. This stored energy is then distributed to prioritized loads during nighttime operation. Loads are divided into three categories based on criticality: communication devices (highest priority), lighting (medium priority), and USB charging/CCTV systems (lowest priority). Each load category is connected through a switching mechanism that enables selective disconnection based on battery status and AI-driven prediction outcomes.

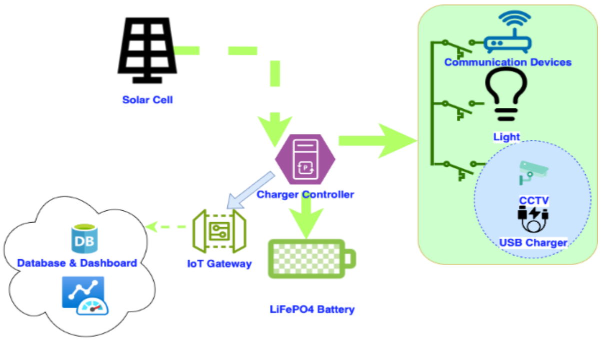

Fig. 1. System diagram of the off-grid solar energy architecture with AI-based load prioritization.

An IoT gateway continuously monitors system parameters, including photovoltaic output, battery voltage/current, and individual load consumption. This gateway is linked to a cloud-connected database and visualization dashboard for real-time data logging and offline model training. Load status and priority control logic are applied using a decision model embedded within the gateway or edge device.

This design supports dynamic load management where essential services are maintained as long as possible under energy-constrained conditions. It enables real-time prioritization decisions based on historical usage trends and forecasted energy availability, central to the experimental simulation and evaluation conducted in this research.

3.2 Data Collection

Measurements of the energy system were taken every 5 minutes in 2024 from a solar installation off the grid in Chiang Mai, Thailand. The monitoring system recorded PV array input, battery parameters (voltage, current, power), and load power consumption categorized by priority tiers. The dataset included more than 105,000 records, averaged to hourly values for seasonal and model analysis.

The data was divided into three operational seasons for experiments based on regional climate: Rainy (May–October), Winter (November–February), and Summer (March–April). This enabled focused training and assessment of predictive models across different solar irradiance and load scenarios.

Data preprocessing fixed gaps and anomalies for reliable analysis. Short-term communication interruptions (≤ 2 hours) had missing values filled through linear interpolation, and transient sensor noise along with outliers were addressed using a rolling average filter (window size = 3). The steps maintained the temporal features of the signals, allowing the dataset to function as a reliable and representative input for evaluations of both AI and non-AI control strategies.

3.3 Data Analysis

Five machine learning models were used in the predictive evaluation: Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machine, and Decision Tree. Models were trained to estimate battery discharge profiles and forecast nighttime support duration using hourly PV generation, battery state, and load demand across priority tiers.

Model development used a seasonal partitioning method. Data from the rainy season (May–October) was utilized for training, while the winter (November–February) and summer (March–April) seasons acted as independent test sets to assess generalization across varying solar resource conditions. To enhance robustness, October was separated from the Rainy season and utilized as a held-out intra-season test set.

K-fold cross-validation was used on the Rainy season training data to evaluate model stability and estimate performance variance across various folds. Two operational strategies were compared in the simulation.

3.3.1. AI-driven load prioritization disconnects lower-priority loads when energy reserves are predicted to be insufficient.

3.3.2. The non-AI baseline keeps all loads active until the battery hits its critical threshold.

Performance was measured with Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Daily support hours exceeding 24 Ah (20% of nominal capacity) were calculated to evaluate system resilience, indicating the capacity to maintain essential loads in low-solar conditions. To quantitatively assess the performance of the predictive model used in this study, we define a set of standard regression evaluation metrics commonly applied in battery discharge prediction and time-series modeling: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2 score). These metrics compare the predicted battery values against observed data, allowing for direct evaluation of model effectiveness in simulating energy availability under varying load scenarios.

Let:

- y_i denote the observed (actual) battery state of charge (in Ah) at time, i
- $\hat{y}_i$ be the predicted battery state from the model at the same time step,
- $\overline{y}_i$ be the mean of all observed values over the dataset,
- n represent the total number of observations.

The Mean Absolute Error (MAE) is defined as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

This metric reflects the average absolute deviation between the predicted and actual battery values, offering a straightforward interpretation of prediction accuracy in the same unit as the variable (Ah).

The Root Mean Square Error (RMSE) provides a measure that penalizes larger errors more significantly:

$$\text{RSME} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{2}$$

This is especially useful in off-grid energy systems where large prediction errors can result in failure to maintain critical loads, thus RMSE helps identify worst-case deviations.

The Coefficient of Determination (R^2) evaluates the proportion of variance in the observed data that is predictable from the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2} \tag{3}$$

A value close to 1.0 indicates that the model explains most of the variability in the battery state over time, demonstrating reliable forecast performance.

In this study, these metrics are computed daily and aggregated to assess both short-term prediction stability and long-term model consistency over the rainy season dataset. These results provide evidence of the model's effectiveness in supporting real-time load control decisions and validate its suitability for integration into energy-limited IoT-based solar systems.

We used Random Forest Regression as it effectively captures non-linear relationships and reduces overfitting. Grid search tuned key hyperparameters: number of estimators (n=100–500), maximum depth (3–10), and minimum samples per leaf. A 5-fold cross-validation method guaranteed generalisation. Linear Regression and Support Vector Regression (SVR) were assessed for baseline comparison. Random Forest consistently surpassed the alternatives in MAE and RMSE throughout the entire dataset.

3.4 Data Validity and Reliability

We verified the predictive performance of each machine learning model through season-specific and overall error analysis on the complete dataset. We calculated accuracy metrics like R^2, MAE, and RMSE for both training and test sets to verify model generalization. Seasonal k-fold cross-validation evaluated result consistency across different data subsets, ensuring statistical reliability. Simulated outputs were compared with actual system load thresholds to confirm operational reliability in real-world conditions. Daily performance tracking of the Rainy, Winter, and Summer datasets showed consistent model behavior over time, with little variation in prediction accuracy. This layered validation method guarantees the reliability and reproducibility of the suggested AI-driven load prioritization framework in actual off-grid solar energy settings.

3.5 *Research Limitations*

This work utilized data covering all three seasonal conditions however, the analysis was performed entirely in a simulation environment without deployment to physical hardware. As such, real-time performance under embedded controller constraints and varying field conditions has not yet been verified. Future studies will focus on edge-based implementation and adaptive control strategies to validate operational reliability in live off-grid solar systems.

4. RESULT AND DISCUSSION

Figure 2 shows the battery charge level (in Ah) recorded during the rainy season in an off-grid solar energy system lacking AI-based load prioritization. The dashed horizontal line indicates the critical battery threshold of 24 Ah (20% of total capacity), below which essential loads may be interrupted. The trend shows several instances where the battery fell below the safety threshold, especially during overcast or low irradiance days. Mid-season, battery level fluctuations are more noticeable, showing a greater mismatch between energy generation and load demand. Without intelligent load shedding, discharge speeds up, operational runtime decreases, and critical loads risk losing service. These findings highlight the need for predictive load management techniques like AI-based prioritization to ensure system stability and safeguard energy availability in challenging environmental conditions.

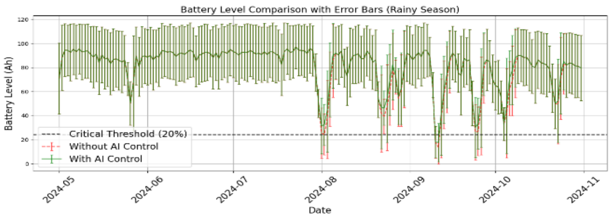

Fig. 2. Daily battery level profile without AI load control during Rainy season.

Figure 3 shows the hourly distribution of power consumption for prioritized electrical loads during the rainy season. The stacked area chart divides total load into three categories: communication devices (Internet & Network), lighting systems, and auxiliary loads (CCTV and USB charging). These categories align with first-, second-, and third-priority load classes. The visualization shows steady baseline usage from high-priority communication devices, whereas lighting and auxiliary loads display greater fluctuations, especially in the early evening and nighttime. The third-priority group, CCTV and USB, exhibits the most variability and highest peak values, posing a challenge for energy-constrained battery systems. The stacked load profile highlights the need for tiered load management, as the total demand during low photovoltaic generation can surpass the system's storage capacity. This figure's analysis supports AI-driven load shedding strategies that extend battery life by temporarily reducing lower-priority loads when storage falls below set thresholds.

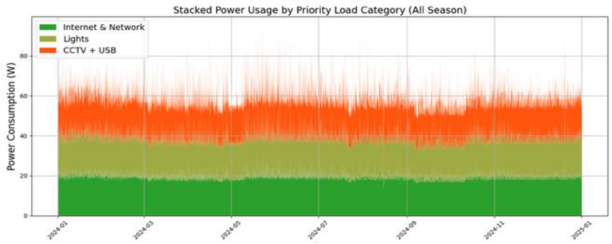

Fig. 3. Stacked power usage by priority load category during the Rainy season.

Table 1 shows the predictive performance of GradBoost, Decision Tree, Random Forest, LogReg, and SVM-RBF, trained on rainy-season data and evaluated on the Rainy, Summer, and Winter seasonal subsets. Model accuracy and macro-averaged F1-score (F1_macro) are presented to reflect classification precision and recall across load cut-off priority classes. Throughout all seasons, GradBoost and Decision Tree recorded the highest F1_macro scores in the Rainy season, demonstrating effective class balance management in the training domain. Most models-maintained accuracy values above 0.96 across all test scenarios, but the F1_macro metric shows significant variation, especially in the Winter season due to class imbalance affecting classification robustness. Models like Random Forest and GradBoost showed high accuracy in both Summer and Rainy conditions, indicating good generalization to varying photovoltaic generation profiles. The perfect accuracy in summer for all models except Decision Tree shows high solar availability and less variability in load cut-off events during this time.

The results show that while accuracy indicates nearly perfect performance, F1_macro reveals important insights into seasonal class distribution effects, especially in Winter, where low irradiance results in fewer cut-off events and potential bias towards majority classes.

Figure 4 shows a comparison of five machine learning models: Gradient Boosting, Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine with RBF kernel, assessed using seasonal datasets for Rainy, Summer, and Winter conditions. Every data point represents the model's performance for a particular season, with Accuracy on the horizontal axis and the macro-averaged F1-score on the vertical axis.

Table 1. Performance comparison of 5 machine learning models for battery discharge prediction.

Model	Season	Accuracy	F1_macro
GradBoost	Rainy	0.992527	0.91212
DecisionTree	Rainy	0.990036	0.831887
RandomForest	Rainy	0.98981	0.788192
LogReg	Rainy	0.980978	0.376105
SVM-RBF	Rainy	0.979846	0.32994
LogReg	Summer	1	1
RandomForest	Summer	1	1
SVM-RBF	Summer	1	1
DecisionTree	Summer	1	1
GradBoost	Summer	0.999308	0.499827
DecisionTree	Winter	0.964113	0.418604
GradBoost	Winter	0.965148	0.349394
LogReg	Winter	0.967219	0.327779
RandomForest	Winter	0.967219	0.327779
SVM-RBF	Winter	0.967219	0.327779

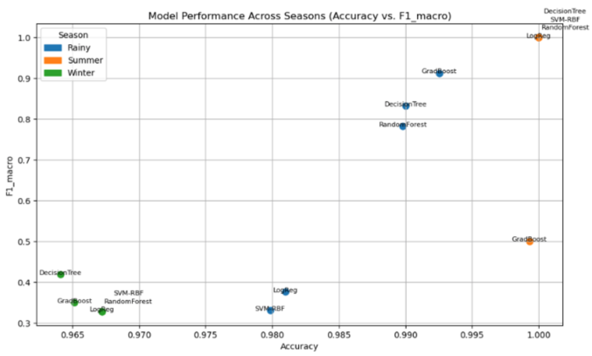

Fig. 4. Accuracy vs. F1-Score comparison across seasons.

The plot shows that models like Gradient Boosting, Decision Tree, and Random Forest consistently reach high accuracy and competitive F1-scores during the Rainy season, where the variability in solar generation creates tougher prediction challenges. Summer results show consistently high accuracy across all models, with slight variations in F1-scores, indicating stable solar availability. Winter season performance shows lower F1-scores across all models, with Decision Tree and Gradient Boosting demonstrating slightly better resilience.

The results show that accuracy stays high throughout the seasons, but the F1-score provides a better understanding of model strength during seasonal changes, especially in difficult or unbalanced prediction situations in off-grid solar energy management.

Figure 5 shows the predictive accuracy of five regression models during rainy, summer, and winter seasons using MAE, RMSE, and R² metrics. Random Forest Regression shows the lowest error values and highest R² scores across all seasons, highlighting its strong generalization and adaptability to seasonal changes. Decision Tree Regression achieves competitive accuracy, especially during rainy and summer periods, but exhibits higher error variance in winter. Gradient Boosting shows decent performance, performing well in summer but displaying increased MAE and RMSE in rainy and winter conditions. Linear Regression and SVR show the poorest performance, with higher error rates and lower R² values, indicating their limited ability to model the dataset's nonlinear relationships. These findings emphasize the benefits of using ensemble methods for predicting energy in off-grid solar systems during seasonal changes.

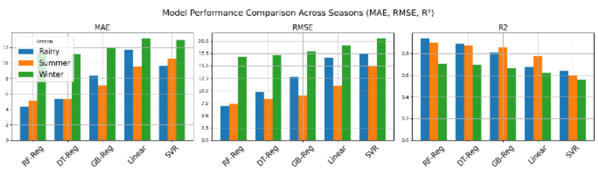

Fig. 5. Model performance comparison across seasons.

Figure 6 shows the stability evaluation of five classification models during rainy season conditions with 5-fold cross-validation. Random Forest, Gradient Boosting, SVM-RBF, and Decision Tree show high median accuracy and tight interquartile ranges, reflecting strong performance and minimal sensitivity to changes in training data. Logistic Regression shows significant accuracy variation and a lower median, underscoring its shortcomings in capturing the nonlinear and complex patterns typical of energy consumption and generation data this season. These results indicate that ensemble and kernel-based approaches provide better stability in ensuring prediction accuracy amid changing weather and energy supply conditions.

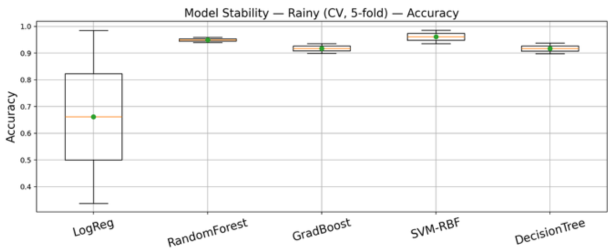

Fig. 6. Rainy season model stability (5-fold CV).

Figure 7 shows the accuracy distribution for five machine learning models Logistic Regression, Random Forest, Gradient Boosting, SVM-RBF, and Decision Tree, assessed with 5-fold cross-validation in the winter season. All models show narrow interquartile ranges, reflecting consistent performance across folds. The median accuracy for most models is about 0.92, with Random Forest and SVM-RBF displaying slightly higher upper limits, indicating a bit better best-case performance.

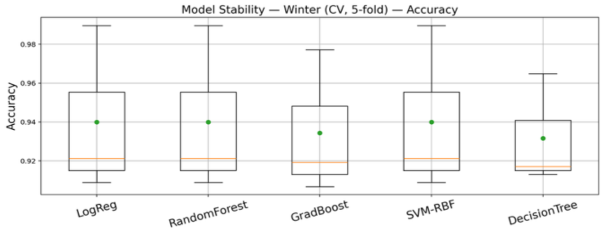

Fig. 7. Winter season model stability (5-fold CV).

Gradient Boosting and Decision Tree show similar averages but with wider ranges, whereas Logistic Regression has competitive accuracy but more variability in results. These findings show that in winter, when solar energy is less available, models perform consistently with little variation, demonstrating their reliability in challenging energy conditions.

Figure 8 shows the stability of five machine learning models through cross-validation in the summer season. Compared to the results in Table 1, all models show perfect or near-perfect accuracy, with most achieving an accuracy of 1.0 and a high F1-macro score for this season. The lack of variance in the cross-validation plot matches these metrics, showing that the models predicted load cut-off priorities accurately in the summer dataset.

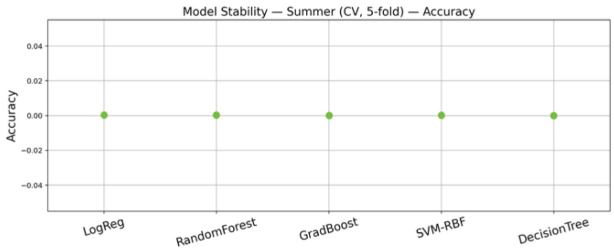

Fig. 8. Summer season model stability (5-fold CV).

Figure 9 shows the cross-validation stability of five machine learning models, comparing their accuracy across rainy, winter, and summer seasons. Accuracy values are presented as mean ± standard deviation for each season, offering insight into predictive performance and consistency. Results show that model stability changes greatly with the seasons. During summer, all models reached perfect accuracy with minimal variance, showing a highly predictable environment thanks to steady solar energy supply. Winter results stayed strong across all models, but showed a bit more variability, indicating moderate changes in solar generation. The rainy season showed significant differences, with models like Random Forest, Gradient Boosting, and SVM-RBF remaining stable, whereas Logistic Regression had lower mean accuracy and the highest variance. These findings indicate that some models maintain high performance despite seasonal changes, but the rainy season brings increased uncertainty, likely from variable solar irradiance and greater battery resource demands.

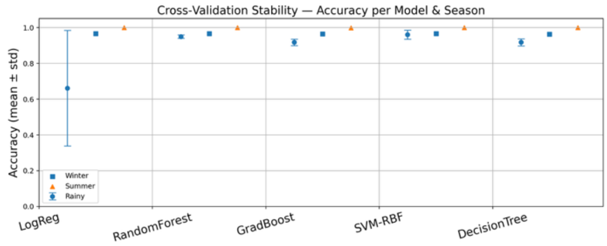

Fig. 9. Cross-validation stability of model accuracy across seasons.

The experimental results show that model performance in optimizing load cut-off priority varies by season, with environmental conditions affecting predictive stability and accuracy. During summer, all models reached perfect or nearly perfect accuracy with minimal variance, showing a stable prediction environment thanks to consistent solar generation and fewer fluctuations in battery discharge patterns. Winter performance was solid for most models, though some variability was noted due to occasional drops in PV input. The rainy season presented significant challenges, leading to notable accuracy declines and increased variance, especially for Logistic Regression. This indicates that simpler linear models have difficulty in conditions of frequent low irradiance and irregular load demands.

The results support the initial hypothesis that AI-based optimization can enhance battery life, particularly in variable energy conditions. Ensemble methods [24] like Random Forest and Gradient Boosting consistently surpassed other models throughout all seasons, ensuring greater stability and predictive accuracy. This highlights the gap in the literature, showing that there has been little exploration of optimization strategies for off-grid energy systems tailored to specific seasons. Seasonal differences emphasize the need for context-aware control strategies, indicating that static cut-off thresholds might be less effective than adaptive, AI-driven approaches.

These findings enhance the theoretical framework by demonstrating that ensemble learning models offer a stronger solution for energy management in fluctuating solar conditions, thereby improving nighttime load support. The findings create avenues for future research, like combining hybrid ensemble techniques with real-time sensor input to enhance adaptability. This method could allow for flexible, season-sensitive cut-off strategies that enhance energy availability and extend battery life. The methodology can also extend to other renewable-powered microgrids, paving the way for more resilient and efficient energy management solutions.

5. CONCLUSION

This research analyzed AI-driven load cut-off prioritization for an off-grid solar energy system in Chiang Mai, Thailand, through a comparative assessment of five predictive models. The results show that seasonal factors significantly impact model performance, with the optimized model consistently providing better predictive accuracy, stability, and reliability in forecasting battery support time. These findings enhance the field by demonstrating that season-aware predictive modeling can greatly optimize energy management for off-grid systems, minimizing the risk of early battery depletion and prolonging nighttime availability.

These results are important for sustainable energy management. Optimizing load allocation allows critical services to run smoothly without the need for expensive hardware upgrades. AI-driven prioritization frameworks can extend beyond rural electrification to other critical areas, like maintaining uptime for telecom cell sites, supporting vital medical equipment, or ensuring continuous operation in industrial facilities. This broadens the use of AI load optimization from residential off-grid systems to essential infrastructures.

The research has certain constraints. The dataset was limited to one site and one year of seasonal data, potentially missing variability over longer periods or different geographic areas. The results show strong evidence from simulation, but real-world deployment on embedded hardware hasn't been tested yet, raising concerns about latency and energy consumption in practice.

Future enhancements should involve testing across diverse datasets over multiple years and sites to improve generalizability, along with implementing optimized models on embedded controllers for real-time assessment. Implementing adaptive control mechanisms can enhance resilience in fast-changing environments. The findings advocate for integrating AI-driven energy management systems into rural electrification and renewable microgrid policies, promoting stable and dependable power access. These methods enhance energy efficiency, extend battery life, and minimize disruptions in residential and industrial off-grid settings.

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